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INTUITION MACHINES: COGNIZERS IN COMPLEX HUMAN-TECHNICAL ASSEMBLAGES

Abstract

The urgency of environmental, security, economic and political crises in the early twenty-first century has propelled the use of machine vision to aid human decision-making. These developments have led to strategies in which functions of human intuitive processing have been externalized to ‘vision machines’ in the hope of optimized and objective insights. I argue that we should approach these replacements of human nonconscious functions as ‘intuition machines.’ I apply this approach through a close reading of artworks which expose the hidden labour required to train a machine. These artworks demonstrate how human agency shapes the ways that machines perceive the world and reveal how values and biases are hardcoded into nonconscious cognitive machine vision systems. Thus, my analysis suggests that decisions made by such systems cannot be considered fundamentally objective or true. Nevertheless, artworks also exemplify how externalized intuitive processing can still be helpful as long as we refrain from blindly taking the results as a go-signal to take immediate action.

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Among other global threats, climate change provides an urgency to develop new machine vision systems. In 2018 Will Marshall, CEO of Earth imaging company Planet, announced their new vision of “Queryable Earth” to “index physical change on Earth and make it searchable for all.” He claimed that this initiative would “empower people with the insights that drive better decision-making at the speed the world moves” (Marshall). Without this technology, Planet’s product architect Chris Holmes is concerned that something important might be missed: “I fear for the world’s survival if we are not able to get an accurate pulse, MRI scans, x-ray and sonogram for what is happening.” (Planet, *FOSS4G-NA 2018 Keynote: Towards a Queryable Earth* - YouTube) The earth is imagined as a sick human body that can be diagnosed using machine learning models, petabytes of satellite images and other sensory data. It is promised that machine vision will help in making informed decisions for managing the earth’s resources. In another example, the company Faception claims that their machine learning technologies can assess a person’s character based on a single facial image. Their AI solutions are promised to be key in “making the right decisions about the person right in front of you, or on the video screen” (“FACEPTION | About Us”). Among other things, their computer vision technology is intended to ensure safety by providing predictive screening solutions that enable preventive actions. Thus, it has the potential to supplement or even replace critical law enforcement officers in completing certain tasks. Faception also foresees its software being used to replace humans in other contexts, for example, when assessing job candidates or insurance applicants. Both examples demonstrate the potential for how computer vision and machine learning technologies can improve human decision-making.

Paul Virilio anticipated that ‘vision machines’ would be capable not only of “recognising the contours of shapes, but also of completely interpreting the visual field” (59). Virilio’s insight was influenced by Frank Rosenblatt’s Perceptron, “the first operative artificial neural network—grandmother of all the matrices of machine learning” (Pasquinelli 6). The revival of neural networks, enabling machine learning, in combination with access to massive amounts of data provides the means for today’s vision machines, thus, we are “delegating the analysis of objective reality to a machine” (Virilio 59).

As machines learn to analyse images and connect them with meaning, they become technical cognizers, in other words actors interpreting data. In her book *Unthought*, N. Katherine Hayles re-thinks the concept of cognition, offering an extended definition which includes biological as well as technical cognizers: “*Cognition is a process that interprets information within contexts that connect it with meaning*” (22; emphasis in the original). Accordingly, cognitive processes take place both in the conscious and the nonconscious. Hayles draws parallels between human and technical nonconscious cognition as they perform similar functions. Contemporary vision machines perform in complex cognitive assemblages in which technical and human cognition weave together. Therefore, it becomes important to understand the interfaces across which non-conscious cognition surfaces to higher-level conscious decision-making.

In this paper I propose that vision machines aiding decision-making are also ‘intuition machines.’ As I will demonstrate intuition functions as an interface between nonconscious and higher-level conscious processing. Intuitions are also a source for fast decision-making when conscious capacity is limited. Hence, the concept of ‘technical intuitions’ can be used to understand

entanglements of human-technical cognition in decision-making. However, human and technical intuition are materially different. Human intuition surfaces physically as a gut-feeling whereas technical intuition is expressed as output values. My intention is not to anthropomorphize machines by claiming that machine intuitions are superior or inferior to human intuitions. Rather, by using the term 'intuition machine,' I try to frame to what extent machine vision systems can be seen to "*represent externalizations of human cognitive processes*" (Hayles, *Unthought* 25; emphasis in the original). I will be using the term machine vision in a broad sense, referring to the "registration, analysis and representation of visual data by machines and algorithms" (Rettberg et al. 97) as it is defined in the *Machine Vision in Everyday Life* project in order to analyse broader cultural understandings of machine vision. This definition relates to the concept of machine perception, focusing on methods of computer vision that are applied in machine vision systems.

As intuition machines are making decisions with us and for us it becomes crucial to ask: how do these machines perceive the world? What constitutes the reality of vision machines? I will use artworks (*VFRAME*; *Asunder*; *Hipster Bar*; *Mosaic Virus - Myriad (Tulips)*; *Training Humans*; *ImageNet Roulette*) to exemplify what roles intuition machines play in decision-making. Through my analysis of several artworks that use and reference machine vision, I highlight both the potential and limitations of intuition machines. Several works, for example, challenge the politics of assembling training datasets or collections of labelled images. The images in relation to their given labels are central in how machine vision systems perceive the world. The very function of nonconscious cognition is to filter. Consequently, everything in an image is flattened to an output value, which

is linked to a label. Although data has to be classified to be put in use, it quickly becomes problematic when humans are categorised as objects.

Human and Technical Intuition—An Interface Between the Nonconscious and the Conscious

In *Unthought* Hayles describes the similarities between the human and technical nonconscious: "Like human nonconscious cognition, technical cognition processes information faster than consciousness, discerns patterns and draws inferences and, for state-aware systems, processes inputs from subsystems that give information on the system's condition and functioning" (11) Furthermore, conscious thinking is dependent on the nonconscious to filter the input of sensorial stimuli from our environment. As an increasing number of sensors are collecting data from our environments, machine learning models are becoming increasingly important in recognizing patterns, filtering and condensing information. Hence, they operate as what Hayles calls technical cognizers in complex human-technical assemblages. In such assemblages, machine vision is not only the enhancement of the human eye, but an externalization of the neuronal processing capacity of the human brain. Nonconscious processes are externalized to machines to optimize human capacity in finding information in a threatening sea of data. Artificial neural networks inspired by, but not identical to, biological neural networks simulate human nonconscious cognition. Cognitive physiology and sciences have revealed that nonconscious processing in humans is one of the sources for intuition.

Intuition is given different meanings in different contexts. It can be described as understanding something unconsciously, sensing the solution, an inner hunch or a feeling, or nonconscious pattern recognition. Research on intuition describes it as experience-based nonconscious processing that requires pre-existing knowledge (Zander et al.; Lewicki et al.). As intuitive processing is nonconscious, it is inaccessible by humans. Hence, nonconscious processes have been difficult to investigate as study subjects are not able to explain “how they *learned* all those information-processing algorithms and heuristics that are involved in the cognitive ‘software’ that is indispensable for their psychological functioning” (Lewicki et al. 796). In a similar manner the nonconscious processes in hidden layers of artificial neural networks are inaccessible to humans. Thus, it is difficult for us to understand what a machine perceives.

In the research field of judgment and decision-making, it has been understood that “intuition means to non-consciously understand environmental patterns and to act according with this first impression without being able to justify it” (Zander et al. 4). However, in this context intuition research has historically been dominated by two conflicting approaches which conceptualize intuition in different ways. The ‘heuristics-and-biases’ approach emphasizes the imperfection of human intuition and considers that heuristics, limited to intuitive predictions, “sometimes lead to severe and systematic errors” (Kahneman and Tversky 237). The more positive ‘fast-and-frugal-heuristics’ approach considers intuition to be a valid, even successful, strategy “when time and cognitive capacity is limited in a fuzzy real world” (Zander et al., 4). However, there is considerable agreement that intuition operates in a two-systems framework that consists of the fast, automatic, effortless,

associative, and non-flexible nonconscious and the slower, serial, effortful, deliberately controlled, and relatively flexible conscious (Price and Norman). Research on creativity and problem solving, however, offers a third approach: “intuitive feelings are seen as a manifestation of a vital component of consciousness that functions as an interface between the nonconscious and the conscious” (Price and Norman 33). Following this approach intuition is a result of nonconscious processing that as a subjective experience (gut-feeling) provides inaccessible reduced information directly to our consciousness. Likewise, when we externalize nonconscious processes to vision machines, the output in the form of reduced information (e.g. object detection: 89% apple; face recognition: 75% female; or emotion detection: 0.945 happy) can be seen as technical intuitions. Thus, technical intuitions function as an interface between the nonconscious processes in the machine and higher-level human or technical cognizers. In a human, the non-conscious and the conscious are attached to the same body, and intuitions provide a partial connection between them. In contrast technical intuitions function as an interface between technical and human cognizers. Furthermore, in automated decision-making technical intuitions serve as input for higher-level technical cognition.

The Role of Reasonable Doubt in Interpreting Technical Intuitions

Contemporary digital artworks demonstrate that intuition machines can be used to enhance human nonconscious capacities in successful ways. However, technical intuitions need to be met with reasonable

doubt. *VFRAME: Munition Detector* (2017) by artist Adam Harvey is an example how the results of an intuition machine can be used as evidence after a detailed process of cross validation. Exhibited as an artwork, *VFRAME: Munition Detector* is an open source computer vision tool to detect illegal munition in vast amounts of uploaded videos. It exemplifies an intuition machine in which technical intuitions function as an interface between the technical nonconscious and conscious human decision-making. It is also a project that recognizes how both human and technical cognizers operate in uncertainty with a limited amount of information, hence, “interpret ambiguous or conflicting information to arrive at conclusions that are rarely if ever completely certain” (Hayles, *Unthought* 24).

According to *VFRAME*'s website, human resources and capacities to process large amounts of visual data are limited. “Human rights researchers often rely on videos shared online to document war crimes, atrocities, and human rights violations. Manually reviewing these videos is expensive, does not scale, and can cause vicarious trauma. As an increasing number of videos are posted, a new approach is needed to understand these large datasets” (*VFRAME: Visual Forensics and Metadata Extraction*). The old approach was hindered by slow conscious human interpretation that required considerable effort to find relevant video material. Thus, the new approach needed to entail capacities of nonconscious processes: fast, automatic and effortless. The solution, to create an object detection tool, led to the outsourcing of cognitive processing into a machine. A machine learning model was trained using labelled data based on a taxonomy, which considers that cluster ammunition can appear in many different ways and be found in altering surroundings. However, the accuracy of trained machine

learning models remained low until synthetic training data, in the form of photorealistic 3-D models, were used to expand the training dataset.

As an intuition machine *VFRAME: Munition Detector* composes only a small part of a whole human-technical assemblage. This particular machine vision assemblage includes other technical cognizers and infrastructure such as photo sensors, smart phones, Internet infrastructure, storage media, data centres, distribution platforms and machine learning algorithms. Human cognizers in the assemblage involve among others witnesses, citizen journalists, activists and those developing, maintaining and controlling access to technical frameworks.

In *VFRAME: Munition Detector* technical intuitions surface from the nonconscious as the desired object, with required confidence, is found and as a result flagged by the software. However, at this point it is uncertain if the video really documents illegal use of munition. The technical intuition is fed forward to further conscious cognitive processes which take place when researchers find, validate and archive the use of illegal munition. The validation process of cross-referencing the evidence to location, time and other metadata and comparing it with related visual material (e.g. satellite images) is a tedious process done manually by the researchers. Each technical intuition *VFRAME* produces is met with reasonable doubt. Nevertheless, the gap between intuition and decision is used to process that doubt. Only by collecting supporting metadata can researchers present flagged material as evidence with sufficient confidence. Finally, the material is archived with the objective to use it as an evidence tool for legally implementing justice and accountability (*About | Syrian Archive*).

Approaching vision machines as intuition machines reveals the need for authenticating evidence in order to make

determinations beyond a reasonable doubt. Although human gut-feeling and technical intuitions are expressed in drastically different ways, both embody a level of uncertainty. However, human intuitive processing “as reflecting cognitive processing on the *fringe of human consciousness*” (Zander et al. 3) allows us to hesitate and question the results of our intuition. Technical intuition on the other hand is expressed as what Louise Amoore describes as a “single output of a machine learning algorithm” and often “as a decision placed beyond doubt; a risk score or target that is to be actioned” (Amoore 149). In other words, in cognitive machine vision systems the gap between intuition and decision does not always allow for reflection or doubt. However, as Amoore argues: “In the science of machine learning algorithms the doubts of human and technological beings nonetheless dwell together” (147). The successful application of an intuition machine is not dependent solely on the accuracy of a machine learning model. *VFRAME* exemplifies how important it is to consider how to handle the uncertainty of technical intuitions as part of complex human-technical cognitive assemblages.

Mind the Gap—When Things Stay Undecidable

Sometimes the gap between intuition and decision-making is filled with conflicting interests, which leads to difficulties in making decisions. Furthermore, decisions are always made with some level of uncertainty. No matter how much data we collect we can still miss something potentially relevant. Training machines on constantly increasing amounts of data is a race for accuracy, however, this can delay decision-making. *Asunder* (2019)

by Tega Brain, Julian Oliver and Bengt Sjölen is an artwork that demonstrates how uncertainty and doubt become a hurdle for making any decision. As a speculative posthuman intuition machine, *Asunder* (2019) proposes large-scale interventions to preserve the earth. Satellite images of rapidly changing geographical sites are used to generate “fictional geoengineering proposals” based on what is best for the planet (“Hack the Planet”). Human financial interests are not taken into account as part of the analysis. Sites such as San Francisco, Vienna, Dubai, the Arctic and the Amazon are presented as cases on the installation’s three panels. The first panel shows historical satellite images of the displayed case, for example, Rondônia, Brazil, one of the most deforested places in the Amazon. Simultaneously on the second panel case data is displayed including environmental changes and their impact. In the case of Rondônia, the following results are listed: soy cropping, deforestation, freshwater pollution, supply-chain emissions, agricultural C4H emissions, warming and fresh-air reduction.

Next, the nonconsciousness of the *Asunder* supercomputer performs pattern recognition on satellite images from the past and the present from sites across the world. Technical intuitions in this case are generated by a GAN (Generative Adversarial Network) as surreal composite images. Several of these possible “region modification options” are displayed as images on the second and third panels. The system then chooses one of the generated possibilities and “analyzes the land use changes in it, and inputs that data into a climate model to estimate how the change would impact the environmental performance of the earth overall” (“Hack the Planet”). Hereafter the second panel changes. Instead of satellite composites graphs of climate change models are displayed. The technical intuition as a final output is

reduced to a line of text on the second panel reading RECOMMENDATION: immediate reforestation.

Brain one of the artists behind *Asunder* questions the limits of 'AI for Earth initiatives' in her paper "The Environment is Not a System." She argues that machine learning models used to analyse the environment will always be limited to datasets that cannot encapsulate the complexity of various ecologies. Earth imaging companies like Planet (introduced earlier in the article) promise "geospatial insight" as they are able to collect increasing amounts of data. However, Earth sensing technology will always be limited as everything cannot be translated to data. There is always a chance we miss something essential. The human nonconscious cannot perceive everything, but neither can a machine, thus, decisions need to be made without absolute certainty. Nevertheless, companies like Planet gain from uncertainty because this provides justification to launch more satellites to the orbit, collect more data and develop machine learning models with better accuracy.

For a crisis like climate change, there is a temporal aspect. As Wendy Chun explains, with predictions come the notion of future. As predictions are fulfilled, they are proven true. However, in case of climate change models, for example, the decisions to be made and the actions to be taken should prevent the predictions (Chun 90–91). There is no doubt that Planets' monitoring products can help to identify illegal deforestation and changes in land use. Moreover, their envisioned intuition machines like Queryable Earth will most likely be able to detect objects in satellite images. Delivering promised 'insight' to "how many trees are there in the Amazon?" and how many have been felled between this week and last week (Planet, *TED 2018 - Planet CEO Will Marshall on Queryable Earth*). One of Planet's environmental manager

applications might even recommend "immediate reforestation" of the Amazon. From the technical nonconscious of this environmental manager surfaces something we already knew, human habits of deforestation in the Amazon are destructive for its environments, hardly an insight in terms of an "unexpected apprehension of the solution." (Zander et al., 1) The intuition machine can encourage better decision-making, yet it does not ensure that better decisions will be made or action will take place (e.g. planting trees).

The histories of colonialism and imperialism as well as the ongoing exploitation of marginalized communities are sources of our contemporary environmental challenges. Acknowledging how environmental resources have been exploited in the past, Brain thinks that "there is no reason to suggest that AI technologies built and implemented by a cohort of wealthy white men in the US will in any way manage or distribute environmental resources in ways that are equitable for everyone" (158). The speculative posthuman technical intuitions *Asunder* produces are not in line with many corporate and government interests as it prioritizes ecological agendas over financial goals. Certain corporations and governments continue to prosper as the gap between intuition and decision becomes undecidable. History shows that doubts can also become a strategy. For example, the philosopher Lee McIntyre traced post-truth strategies to demonstrate how the tobacco industry established a blueprint of strategies to question 'the truth.' Unyieldingly questioning a close consensus of scientific research that smoking is harmful, the tobacco industry advocates managed to delay political decisions and regulations. Since then similar tactics to plant doubt have also been used in the context of climate change denial to influence political positions for the gain of corporate interests (McIntyre).

Chun calls our attention to the gap between the prediction and the future: “if we use programs and habits to help save the future—to fight the exhaustion of planetary reserves, etc. —we must frame the gap between prediction and the future as calls for responsibility, rather than potential errors or truths.” (90) *Asunder* demonstrates how intuition machines are part of human-technical cognitive assemblages in which decision-making powers are distributed throughout the system. Although the gaps between technical intuitions and decisions are important spaces for reflection the quest for more accurate truths can also become a strategy to avoid taking responsibility. If it is irresponsible to stretch the gap and avoid the decisions leading to actions, it can be equally harmful to erase the gap. When intuition machines are automated to make clear decisions quickly rather than making the correct one, then we are at the core of what Luciana Parisi calls ‘technological decisionism’ (1). When we are forced to accept the choices of an algorithm without any space for reflection or doubt, then the responsibility of making decisions is shifted to the machines.

When intuition machines deny credit, reject job applicants, or flag a person as suspect based on their appearance, there is no gap for doubt between the surfacing intuition and action. The algorithm decides for us. Max Dowey’s satiric artwork *Hipster Bar* (2015) exemplifies how technical intuitions function as actuators of automated decision-making. To gain access to drinks in the *Hipster Bar*, customers need to pass as 90% hipster when screened by facial recognition. This intuition machine was trained on 5,000 faces tagged as #hipster on Instagram. After being trained, similar to humans, the machine’s nonconscious links certain facial features or accessories with the characteristics of a hipster. Technical intuitions are expressed as subjective ratings (e.g. 92% hipster). The

machine is automated to make a decision based on the given intuition by the rule: if more than 90% hipster, then allow access to the bar. When enabling or disabling certain actions become automated in everyday life, then as Chun declares “Code as law is code as police.” Or put another way, the machine is delegated the power to both create (meaning) and enforce (judgment). This is a relatively simple example of how the artist as programmer becomes the lawgiver assigning absolute authority, in this case enabling access to a service.

As described human agency is crucial for intuition machines to operate. Hayles suggests that we think of these systems as having ‘punctuated agency’ (*Unthought* 32). In *Hipster Bar* periods of human agency are required, for example for design and development of the application and tasks like collecting and assembling the training sets for machine learning. Although the latter is mostly hidden labour, it is nevertheless often required in order to achieve shorter intervals of machine autonomy. In the case of *Hipster Bar*, the machine is autonomously accepting or rejecting a visitor’s access to the bar.

In the following I focus on the periods of human agency that shape the ways intuition machines perceive the world. In this paper I am discussing the implicit manual labour of assembling training sets, which is only one element of machine learning that shapes how vision machines perceive things. Hence, I acknowledge that my exploration of questions related to intuition machines are limited to supervised learning that usually makes use of human-labelled data in contrast to techniques of unsupervised machine learning. Adrian Mackenzie who writes about machine learners referring both to humans, machines and human-machine relations notes how “machine learning textbooks often warn or enthuse about the profusion of techniques, algorithms, tools, and machines.”(75)

Focusing on training datasets and the labour required to assemble them does not imply that developers, statistics, modellers and other subject poisons (that Mackenzie sets out to maps in order to understand the operational formations associated with machine learning) are irrelevant in shaping how machines perceive their environments. Therefore, perspectives presented in this paper might also be applied to other machine learning approaches, however, this would probably require a compilation of technical questions specific to e.g. architectures of neural networks or vectorizing operations.

Artists Shaping the 'Umwelts' of Intuition Machines

Hayles adapts the term 'umwelt' from Jakob von Uexküll's studies in biosemiotics to understand a computer's internal milieu ("Can Computers Create Meanings?"). Umwelts refer to subjective universes through which every organism or, according to Hayles, technical device makes sense of the world. According to Hayles we can never have an embodied understanding of how another species, including technical beings, sees or understands the world. Nevertheless, the umwelt of humans and other species overlap. Therefore, by accepting the limits of never fully understanding how machines perceive the world we can still unravel ways the umwelts of humans and machines overlap. Artists who train machine learning algorithms themselves are selecting, collecting, categorising, classifying and cleaning datasets. These tasks are also part of developing commercial machine vision applications that perform object and face detection in our everyday lives.

Anna Ridler's artwork *Mosaic Virus* (2018) is a one screen video installation displaying machine-generated "botanical impossibilities" (Ridler). The subtle changes that animate the blossoming of tulips are connected to the fluctuating value of bitcoin. *Mosaic Virus* is exhibited alongside with the *Myriad (Tulips)* (2018), a dataset containing images of 10,000 (a myriad of) tulips. This dataset of images was used to train a generative adversarial network (GAN) to generate novel images of tulips.

The labelled images in the tulip dataset, covering a large wall, implies the tedious work of categorising and classifying involved in training machines to learn algorithms in order to recognize patterns. The artist confirms this in an interview: "This was an insane amount of work and it is usually work that is hidden" (Ridler qtd. in Lee). In the process of collecting the dataset, she describes how she searched for striped tulips at flower markets all over the Netherlands. Selecting the tulips was one decision along the chain of decisions the artist made shaping the output. Ridler explains how she consciously changed the output she wanted by changing the shape and colour of tulips she was buying. Choices were also made when the dataset was cleaned and unwanted 'dirty data' was excluded from the final data set. This is especially relevant when a dataset is collected by scraping images based on a tag, such as the case with *Hipster Bar*. As Dovey was harvesting all of the images labelled hipster from Instagram, he ended up with pictures of dogs, avocados and coffee cups. If he would have used all of those images, the accuracy of his facial recognition application would be insufficient. Therefore, to achieve desired accuracy a dataset needs to be cleaned. As Ridler created her own dataset much of the sanitizing work was done in the process of choosing the camera settings and background as well as the cropping of

the image. In both cases, be it cleaning a scraped dataset or producing it, the choices have an effect on the accuracy of the output.

Each of the images in Ridler's *Myriad (Tulips)* dataset is intentionally labelled with the handwriting of the artist. This is to emphasize the human element in categorising and classifying training sets. "What colour, what type of tulip, how striped it was, whether it was in bud or dying" defined the categories in Ridler's taxonomy, hence, each image was identified and classified accordingly. However, what Ridler classified as 'yellow' someone else might have called 'orange.' Although it sounds straightforward to label objects like tulips based on their appearance, Ridler found it difficult to decide when a "thing is a thing." If it's difficult for something as simple as a flower, she questioned, "imagine how difficult it will be for something as complex as gender or identity!" (qtd. in Lee). This statement brings us to the source of why assumptions that AI is neutral or objective are myths. Moreover, when intuition machines become part of our everyday lives, artists question "who gets to decide what images mean and what kinds of social and political work those representations perform" (Crawford and Paglen, *Excavating AI: The Politics of Images in Machine Learning Training Sets*).

Intuition Machines: Neither Neutral Nor Objective

Kate Crawford and Trevor Paglen excavated hundreds of computer vision training sets for an exhibition called *Training Humans*. The artists describe how their research into the structure and organization of training sets unveiled how the overall taxonomy, the individual classes and each individual labelled image, are all infused with politics. Crawford

and Paglen are concerned that "bad politics are being imported into AI systems today, but treated as somehow neutral and objective" (Crawford and Paglen, "Kate Crawford in Conversation with Trevor Paglen" 22). Objectivity as we know it, has a relatively short history, as the concept was used quite differently before it received its current meaning in the mid-nineteenth century. Since then, in scientific contexts, objectivity has stood for the ability to judge without external influence. Lorraine Daston and Peter Galison have written on the history of objectivity in their study of image production for scientific atlases. They describe how atlas makers sought techniques for creating images seemingly untouched by the human hand. This implies that some aspect of the self needs to be suppressed to achieve objectivity (Daston and Galison). As the automated gaze creates an illusion of suppressed human intervention in the processing and interpreting of images, it may seem that the outcome is more objective. However, as discussed earlier, working with machine learning requires more human labour than we think.

Artists often create their own training sets; however, the accuracy of object detection or facial recognition applications gets better with an increasing number of training data. To save time and resources, researchers as well as companies use publicly available training sets. Artists have problematized several aspects of how these datasets are assembled. For example, Crawford and Paglen's *ImageNet Roulette* (2019) reveals what happens when people are categorised and labelled as objects. In September 2019 a web version of *ImageNet Roulette* was shortly available. Through the web version of the artwork, the user could upload an image. Thereafter, the image was analysed and the resulting technical intuition expressed as green boxes around detected faces, labelled with words such as ballet dancer,

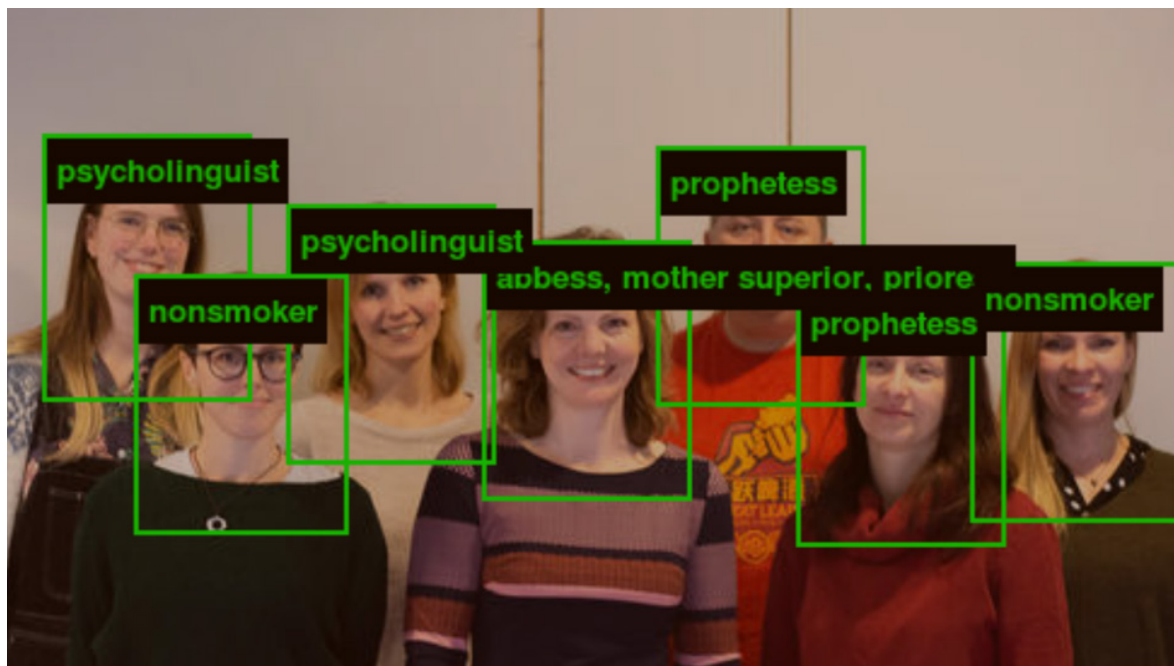


Figure 1: Screenshot of the Machine Vision team at University of Bergen analyzed 20th of September 2019 by *ImageNet Roulette* (web version). Original Photo: Linn Heidi Stokkedal, UiB. All individuals in the photo have given permission to publish this image.

nonsmoker, offender, psycholinguist and so forth. For the artwork a machine learning model was trained using the ‘person’ category of ImageNet, the biggest publicly available training set with more than 14 million labelled images. It is also one of the most used training sets for object detection. As part of my analysis, I uploaded several images to *ImageNet Roulette*. The results I received ranged from the rather neutral ‘computer user’ to disturbing labels such as ‘rape suspect.’ As we uploaded the image of our research team, the results (Figure 1) left us speculating how the machine came to this conclusion.

At the *Training Humans* exhibition, in a live installation version of *ImageNet Roulette*, the visitor was captured by a webcam. When people were detected, the green box with a label was overlaid on the video feed. Moreover, at the exhibition visitors could further examine a selection of

labelled images from the ImageNet database used to train the machine learning model for *ImageNet Roulette*. By taking a closer look at the individual images and their labels, it became evident that the subjective worldviews of the person labelling the images played a noticeable role in how they judged people based on their appearance. Considerable interpretation is needed to define who is a boss, a sleeping beauty, a shopaholic or any other among thousands of labels under the top-level ‘Person’ category of the WordNet taxonomy that was used to classify each individual ImageNet photo.

The ImageNet, like many other datasets, outsourced the labelling to crowdworkers, remotely hired by crowdsourcing websites such as Amazon’s Mechanical Turk. As the workers are sorting “an average of 50 images per minute into thousands of categories” (Crawford and Paglen, *Excavating AI: The Politics of Images in Machine Learning Training Sets*) there is no time to reflect how stereotypes or prejudices might affect one’s choices. Other research reveals that the crowdworkers annotating ImageNet images represent just a few nations: the United

States is overwhelmingly dominant (45.4%) followed by Great Britain (7.6%), Italy (6.2%) and Canada (3%). All of these countries also represent Western worldviews. In contrast, China and India together contribute to just 3% of ImageNet's labels. This makes a difference. For example, Dovey explains how he "slightly naively" thought that his definition of hipster was universal; however, as he was going through the scraped images he realized: "#Hipster has a more global reach, with more Chinese and Asian and Eastern interpretations of the stereotype that were new to me" (qtd. in Bozzi).

Both *ImageNet Roulette* and *The Hipster Bar* are relatively harmless ways to examine the very real concerns involved with automatically assessing people based on appearance. This entire premise, however, is based on the assumption that that our external guise reflects certain characteristics that can be judged and policed. Researchers claim that machine learning models are able to recognize criminal (Wu and Zhang) or gay (Wang and Kosinski) faces. Companies like the earlier mentioned Faception promote their AI technology as able to recognize classifiers such as High IQ, Academic Researcher, Professional Poker Player, White-Collar Offender, Terrorist or Pedophile. These examples are quite extreme and have been contested. Roberto Simanowski warns: "The promise that Faception software will improve human interaction could turn into a nightmare once the product is used beyond airports, subway stations and other enhanced security locations" (viii).

Further concerns have been raised as current AI resembles the work of nineteenth-century photography in the ways bodily measurements are used to identify people especially criminals (e.g. Crawford and Paglen; Agüera y Arcas et al.). This includes the work of French forensics pioneer Alphonse Bertillon, also referenced as the father of the

mugshot. Physiognomists such as Francis Galton and Cesare Lombroso measured and classified people into 'types' based on outer appearance, categorising people according to race, criminality, or deviance from perceived normality. Galton's composite images of the criminal 'type,' composed of superimposed photographs depicting convicted men, carries an eerie resemblance to today's AI generated images of criminal faces. The nineteenth-century assumption that the technical image has a special relationship to the truth in combination with the ideals of physiognomy supported the promotion of scientific racism.

Crawford and Paglen describe how they repeatedly felt shocked as they witnessed how contemporary systems echoed the oppressive traditions of classifying race. For example, in the "UTK Face" dataset, displayed at the *Training Humans* exhibition, race is classified as either White, Black, Asian, Indian or Other, which references the dark histories of racist regimes such as South Africa's apartheid. When race as a physical characteristic is "treated as a matter of fact, written on the body" (M'charek et al. 18) it easily leads to 'phenotypic othering.' In the act of classifying individuals into homogeneous groups our skills to read bodily features are clearly biased. We have been educated to link certain characteristics to targeted groups whereas other groups remain unnoticed. Moreover, research in forensics shows how "different technologies produce different versions of race" (M'charek et al. 11) when the results are translated into evidence. Also, the binary classification of gender into 'man' or 'woman' erases all other possibilities of gender identification and assumes that gender is something fixed. Feminist surveillance scholars have problematized the assumed gender stability in regard to birth certificates arguing that "monitoring occurs with different degrees of specificity and intention

depending on the presumed coherence of gender and sex” (Moore and Currah 59). As race and gender are virtually standard in most available face detection applications, the dataset collections presented in the *Training Humans* exhibition make powerful statements because they expose how reductive technical intuitions can become.

Conclusion

In this paper I approach machine vision technologies as intuition machines. This allows for a reading of contemporary artworks that reveals both the advantages and limitations of computer vision technologies used for judgment and decision-making. In artworks, machine vision is represented as malleable, collapsing any assumptions that these technologies are neutral or objective. However, artworks such as *VFRAME* demonstrate how externalizing nonconscious cognitive processes to machines can be a successful strategy when filtering signals out of noise. Nevertheless, technical intuitions easily become discriminatory if they are automatically executed as law like in *Hipster Bar*. *ImageNet Roulette* and *Training Humans* demonstrate how humans are classified as objects by contemporary machine vision systems. The dangers of intuition machines become more apparent when human characteristics are assessed purely based on appearance, echoing dark histories. My analysis of these artworks demonstrates how values, biases, stereotypes and prejudice are ingrained into a machine’s *umwelt* as the training set shapes how machines perceive and operate in their given environments. This means that we also need to allow a gap between technical intuitions and decisions. A gap to doubt, reflect and question the politics of the machine is crucial. However, as *Asunder*

demonstrates, technical intuitions might be dismissed and questioning the truth becomes a strategy of lingering in the undecidable as some decisions require responsibility to make them.

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